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Linkages Among AI Elements Affecting Quality and Value of Education

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Abstract: Artificial intelligence (AI) has advanced rapidly in recent years and has become widely integrated across various fields, including education. This paper seeks to provide a comprehensive examination of the current state of AI in education by exploring its potential to revolutionize learning experiences through personalized approaches and data-driven multifaceted tools, while also highlighting important challenges that require consideration to ensure its responsible development and implementation. AI shows great promise to personalize instruction for each student based on assessments of their individual strengths, weaknesses, interests, and learning preferences. However, several challenges still necessitate careful examination of AI's implications on education. Issues like algorithmic bias, the digital divide between socioeconomic groups, and concerns around reduced critical thinking skills all require addressing. If not developed and applied judiciously with these challenges in mind, AI risks exacerbating rather than alleviating existing inequities and hindering the cultivation of higher-order cognitive abilities. Through a comprehensive review of the relevant literature regarding AI's current and potential roles in education, this paper identifies several key considerations around learning outcomes, challenges, and implications. Findings from interpretative structural modeling analysis also reveal the importance of balancing AI capabilities with safeguarding against potential downsides like those mentioned above. It is imperative that AI integration in education is approached responsibly with an understanding of both its promise and risks to learning to ensure its successful and equitable implementation for all students.

Keywords: artificial intelligence, systems approach, quality education, value education, personalized learning, interpretative structural modelling (ISM)

1. Introduction

Even for specialists, defining artificial intelligence (AI) can be challenging. One explanation for this is the dynamic nature of AI. As Nick Bostrom, a leading AI expert from Oxford University, explains: "lot of cutting edge AI has filtered into general applications, often without being called AI because once something becomes useful enough and common enough it is not labeled AI anymore" [1]. The fact that AI is an interdisciplinary science contributes to its difficulties in definition. The field of AI benefits from the contributions of anthropologists, biologists, computer scientists, linguists, philosophers, psychologists, and neuroscientists, each of which adds their unique vocabulary and point of view.

The pursuit of creating intelligent machines that replicate human behavior has accelerated with the realization of AI. With the latest advancements in computer science, a proliferation of definitions and explanations of what counts as AI systems has emerged. For instance, AI has been defined as "the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings" [2]. AI dominates the fields of science, engineering, and technology but also is present in education through decision-making systems and algorithm productions [3]. For instance, AI has a variety of algorithmic applications in education, such as personalized learning systems to promote students' learning, automated assessment systems to support teachers in evaluating what students know, and facial recognition systems to provide insights about learners' behaviors [2].

The global adoption of new-generation information and communication technologies, like AI, the Internet of Things (IoT), and blockchain technology, is speeding up the technological and industrial revolution. Academics, businesses, and government agencies have all shown a great deal of interest in AI [4].

As AI continues to grow, so too are its applications in education. These include the potentially exciting possibilities for personalized learning, dynamic assessment, and meaningful interaction in online, mobile, and hybrid learning environments. AI-enabled devices and applications, for example, can automatically generate a student learning profile and give personalized material, feedback, and learning parameters by collecting, aggregating, and analyzing real-time student learning performance data from various sources. In turn, these offer more specialized and pertinent learning opportunities and experiences that help students advance through the course material [5].

Research and education have advanced significantly as a result of AI, offering a range of

applications to improve educational research, instruction, and learning. Here are a few well-known uses of AI:

1) Semantic Scholar
2) HyperWrite
3) ChatPDF
4) Grammarly

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5) Brainly
6) Tutor.AI

While there is a general increase in interest in and expectations for students-AI collaboration in learning, the integration of AI into classroom activities and the curricula linked to AI in K–12 education remain complicated and difficult. Teachers confront difficulties since they are not formally prepared for AI in education (AIEd) and must teach about it in a curriculum that is crowded with material without a clear roadmap for AIEd. Furthermore, teachers face significant pedagogical challenges in designing and facilitating how students interact, collaborate, and learn with AI in the classroom – a setting previously dominated by human–human interaction. Even though AI has the potential to improve teaching and learning for both students and teachers, the ethical and societal implications of these systems are rarely fully taken into account [6]. More provocatively, in response to the teacher shortage in the USA, for example, scholars [7] have proposed to replace some roles of teachers with robots using AI.

AI, with its innovative capabilities, holds significant promise in revolutionizing educational ecosystems by enhancing personalized learning experiences tailored to individual students' needs, facilitating targeted instructional strategies for educators, and empowering administrators with insightful data-driven machine-learning tools. Nevertheless, the deployment of AIEd is not without its share of challenges that necessitate thorough examination and proactive solutions. Striking the right balance between leveraging AI's capabilities to enhance learning experiences and safeguarding against potential risks is crucial for the successful integration of AIEd.

2. Review of Literature

Numerous research have been conducted regarding the uptake and persistence of online or digital learning. The primary research publications that served as the foundation for this study's efforts to create a preliminary list of variables influencing education due to the usage of AI are highlighted in Table 1. Chiu et al. [8] examine literature from the past decade (2012–2021) through matrix coding and content analysis. The results presented the current focus of AIEd research by identifying 13 roles of AI technologies across key educational domains, 7 learning outcomes of AIEd, and 10 major challenges. The review also provided recommendations for the future direction of AIEd research.

Tao et al. [9] summarize research on the challenges of integrating AI and robotics in education. The study was conducted from 2015 to 2019 by the New Granada Military University and involved over 140 teachers in Bogota, Colombia. The research identified teachers' perceptions of applying robotics and AI in the classroom. Key findings from extensive fieldwork focus on the disadvantages and challenges teachers foresee in using robots and AI in educational settings.

Akgun and Greenhow [6] explain that the principles of machine learning and algorithms were used to quickly define AI; applications of AI in educational settings and the advantages of AI systems to enhance students' learning processes were presented; and ethical issues and conundrums associated with the use of AIEd were discussed. By offering instructional materials that instructors can utilize to deepen their students' understanding of AI and ethics, the article aims to support practitioners in navigating the ethical

Table 1
List of factors indicated in various research papers

S. no.	Author	Factors found
1.	Chiu et al. [8]	1) Lack of relevant learning resources for personalized/adaptive learning 2) Selecting appropriate data for AI predictive models 3) Lack of connection between AI technologies and their use in teaching 4) Lack of interdisciplinary AI technologies for learning 5) Worsening educational inequity by widening the digital divide among students 6) Insufficient knowledge of AI technologies among teachers 7) Negative attitudes toward AI among students and teachers 8) Lack of AIEd research on socio-emotional aspects 9) Lack of education perspectives in AIEd research 10) Ineffective evaluation methods of AIEd
2.	Tao et al. [9]	1) Lack of leadership 2) Coldness 3) Passivity 4) Lack of emotions 5) Noncritical thinking
3.	Akgun and Greenhow [6]	1) Privacy violations 2) Algorithm bias 3) Surveillance mechanisms or tracking systems
4.	Mohammad and Watson [10]	1) Cultural granularity 2) Cultural bias 3) Cultural realism
5.	Murtaza et al. [11]	1) Difficulty in feature identification and collection 2) Challenging generation and delivery of adaptable content 3) Lack of knowledge tracing 4) Elicitation of learner's preferences 5) Updating of learner's preferences 6) Feature engineering of learner-content -interactions

challenges and reaping the benefits of incorporating AI in K–12 classrooms.

Mohammed and Watson [6] analyze how intelligent learning environments have evolved their focus from instructional rigor to a deeper emphasis on the learner. Next, it examined some key challenges faced when integrating culturally sensitive design features into intelligent learning environments. The chapter discussed several potential approaches for addressing these challenges, such as teacher modeling, educational robotics, and empathic systems. Important considerations like machine ethics were also highlighted. Murtuza et al. [11] identify requirements and challenges for a personalized e-learning system. It addressed four key questions on personalization factors, state-of-the-art research, AI benefits, and future directions. An in-depth survey answered these through a comprehensive review of existing personalized e-learning solutions. It discussed significant learning models and theories. An efficient five-module framework was proposed: Data, Adaptive Learning, Adaptable Learning, Recommender, and Content/Assessment Delivery.

3. Problem Description

After a careful analysis of the literature, it was found that since AI has been used in education, researchers have become more interested in this field. Numerous studies have confirmed, both qualitatively and quantitatively, the importance of a number of parameters in the adoption, management, and difficulties encountered by teachers and students using AI in classrooms and universities. Scholars, researchers, and decision-makers each have a unique set of perspectives. The Soft Systems Methodology (SSM) is a structured approach to addressing socially perceived problematic circumstances. It is focused on taking action. It arranges thoughts regarding such circumstances so that remedial action can be done. This approach is applied in a pluralistic and complicated environment [12, 13].

Since the components in this research come from a variety of sources, including students, teachers, institutions, and personal aspects, it can be viewed as complicated. There are numerous methods in which any one factor can affect another. As a result, interpretative structural modeling (ISM) analysis was employed in this study as part of SSM to categorize the components and divide them into hierarchical tiers based on their interactions with one another. AI implementation is therefore a complex problem that depends on many variables, and there are probably many related variables acting as a challenge that could be affecting its successful implementation. This model illustrating the relationships between these crucial variables would be extremely helpful to policymakers and decision-makers in defining the focus areas. The goal of the researchers' work is to make it easier for AI-related policies and technology to be adopted and implemented. Furthermore, the existing situation is significantly more accurately described by the pragmatically defined interactions between the elements than by each aspect taken into account independently. The ISM is a useful tool in these kinds of circumstances because it makes it possible to derive the general structure of a system from the relationships among its constituent elements [14].

3.1. Research gap

Previous studies have examined the aforementioned elements separately, without considering their interconnectivity or hierarchical arrangements. The objective of this research endeavor is to address such deficiencies by illuminating the linkages and levels of precedence among said elements, thereby cultivating a more holistic grasp of their interdependences. Specifically, through a mixed-methods analytical approach, both qualitative and quantitative in nature, this investigation seeks to map the dynamic relationships that exist between the identified variables and to parse out their overarching taxonomic framework. It is the hope that such elucidation will advance current knowledge by presenting a more systemic, big-picture perspective regarding the interplay between these constituent parts and how they collectively function as a higher-order construct. The findings aim to fill tangible gaps in the literature and offer novel insights applicable across various relevant domains.

4. Material and Methods

4.1. Nominal group technique (NGT)

NGT [15] is a structured group discussion method used to generate and prioritize ideas or solutions. It encourages equal participation from all group members and ensures that all ideas are considered and evaluated fairly. It is primarily centered upon the idea of consensus building among the domain experts. The selection of experts is crucial who have gained expertise and possess the required experience in the domain. Five to nine experts are sufficient in NGT for discussion. Business firms use this approach to reduce the complex picture of the problem so that the decision-making process can be facilitated by developing a detailed problem scenario and developing an alternative course of action. NGT has been put in association with other tools of systems methodologies under interactive management. NGT generates quantitative data (prioritization through voting) and qualitative data (group discussions), whether it is done in person or electronically [16]. Thus, it has been taken as an essential method of idea generation in systems research. Facilitated by a moderator, the steps of NGT include individual idea sharing, group discussion, voting to finalize the idea, and lastly final decision about any particular idea or point. The optimal composition of an NGT group comprises 4–7 participants, with a permissible range of 2–20 individuals per group [17]. In this research work, 10 experts were invited from academics and technology developer backgrounds (Table 2); they were asked to develop a list of elements of AI impacting the quality and value of education and define a pairwise relationship of influence among identified elements to develop ISM. For this research study, the key stakeholders in the relevant field were initially identified on the basis of the researchers' judgment. Once these major players had been determined, formal invitations to participate in the project were extended. Experts who responded with interest and acceptance to the researchers' outreach were then engaged to directly contribute to and inform the work.

During the NGT session, the facilitator initially displayed a list of factors to the experts for their review and consideration. Table 1 presents the preliminary set of elements that were identified from the

Table 2
Profiles of the domain experts participated in NGT sessions

Profile	Number of experts
Teaching faculties in higher education institute	3
Teaching faculties in coaching institute	2
Researchers in education domain	2
Software developer/engineer	2
Member of education regulatory body	1

literature review, prior to the structured discussion and ranking steps of the methodology. These initial concepts were then discussed, refined, and prioritized by the participants according to their perceived level of importance using the prescribed NGT voting process. Once this evaluation was complete, the finalized set of critical factors determined by the experts through the NGT was presented and documented.

4.2. Interpretive structural modeling (ISM)

Introduced by Warfield [18], ISM is a method used in systems analysis and decision-making to understand complex relationships among elements within a system. It helps in identifying hierarchical structures and interactions among variables or components to prioritize and analyze their impact on each other. ISM aims to uncover the interrelationships and dependencies among various factors or elements within a system or problem domain. It helps in structuring these relationships hierarchically to understand which factors influence others directly or indirectly [19]. This methodology is structural, based on correlation, which extracts an overall structure from a complex set of variables; it is interpretive, as the group's judgment will determine whether and how the various elements are related; it is also modeling, as the specific relationships and overall structure are portrayed in a digraph model; it helps to impose order and direction on the complex relationships among various system elements; and it is primarily intended as a group learning process, as it is applied by individuals. As a result, it enables researchers to create a blueprint that outlines the intricate relationships between numerous components of a system [20].

The interpretation of the model starts from the base level of ISM that contains the most driving element(s) among all, and the subsequent above levels in the hierarchy show the dependent elements. Sometimes, interdependence may also be seen between the elements at the same level. The process starts with the identification of elements and description of influence pairwise among the elements, and then the values under the pairwise relationship matrix are entered into the software that further converts the matrix into initial reachability and final reachability, performs level partitioning, and then finalizes the model. In this research work, the factors influencing the challenge toward quality and value of education were the elements.

5. Findings and Analysis

Identification of elements: On the basis of the factors from the literature review and the discussion in the NGT session, the experts finalized 10 elements (Table 3) to be taken forward for analysis. In the first step, all the factors from the literature review were shown, and experts were allowed to add/delete/merge or split the given factors in the list. The consolidated list of 27 factors was reviewed again, and out of that, 10 elements were formed and finalized for the study. NGT starts with putting up a triggering question in front of the group of experts. The following question was put up for the identification of elements:

> *"What factors do you think act as challenges for quality and value of education considering the usage of AI by the students in their academics?"*

Pairwise contextual among elements: Forming a structural self-interaction matrix (SSIM) is a way to define the column- and row-wise arranged elements. Only the upper diagonal is filled, leaving the same element interaction diagonal as well, based on four relation possibilities: "V" if the row element influences the column element, "A" if the column element influences the row element, X if the row and column elements both influence each other, and O if no association between the two is there. The triggering question for this is given as follows:

Table 3
List of finalized elements

Element number	Element name	Description
1	Reduced critical thinking skills	Students' ability to acquire critical thinking and decision-making skills is limited by their reliance on AI systems.
2	Overreliance on technology	Overuse of AI for learning reduces human intervention in the learning process and creates dependency.
3	Lack of human (teacher–pupil) interaction	Artificial intelligence reduces the vital personal connection that exists between educators and learners.
4	Misalignment with educational goals	The use of AI may not be consistent with the main educational objectives, which could divert attention from long-term learning goals.
5	Manipulation of Information	The accuracy of pupils' knowledge may be impacted by biased or distorted information provided by AI systems.
6	Ethical negligence	The absence of moral standards for AI use could lead to privacy violations and other issues.
7	Algorithmic bias	Algorithm biases in AI could unjustly affect how students are evaluated and have access to educational materials.
8	Superficial knowledge	AI promotes rapid knowledge access, which could lead to surface-level comprehension as opposed to deep learning.
9	Ineffective and unfair evaluation	An assessment that relies too much on AI may produce erroneous results that undervalue students' actual talents.
10	Digital divide	Different socioeconomic groups' already-existing educational gaps are made worse by unequal access to AI-driven products.

"How do you think the elements are associated with each other considering the pairwise selection?"

Computation of results: After the development of SSIM (Figure 1), the matrix values (V, A, X, O) were entered into the SmartISM software [21]. This online software is freely accessible. After entering the matrix values, the software immediately computes the results by converting SSIM into a reachability matrix (binary- 1, 0 form) (Figure 2), and then it performs transitivity checks to make the final reachability matrix (Figure 3). On the basis of driving and dependence power, the elements are divided into four different categories under MICMAC analysis (Figure 4). Further, the transitivity links are removed to form the final model known as ISM.

Developing ISM: Once the model is ready, it is shown to the experts in case of any conceptual inconsistency that may require any rectification. The experts agreed with the generated results and finalized the ISM. Figure 5 is the software-generated final model output. The model has 10 elements divided into six levels ordered from top to bottom.

Figure 1
Structural self-interaction matrix (Source: SmartISM software)

Variables	1	2	3	4	5	6	7	8	9	10
1		A	O	V	O	O	O	V	O	O
2			V	O	V	O	V	O	O	O
3				O	O	O	O	V	O	O
4					A	A	O	A	A	A
5						O	A	V	V	O
6							O	O	V	O
7								V	O	O
8									V	O
9										A
10										

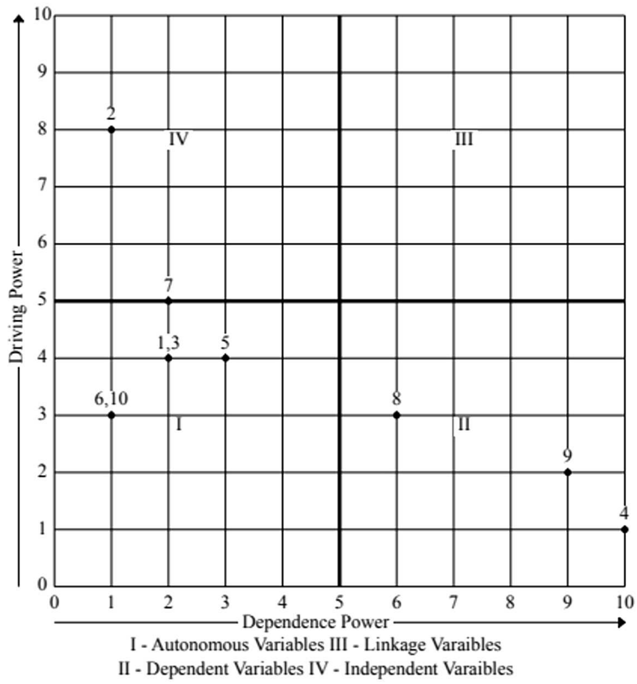
Figure 2
Reachability matrix (Source: SmartISM software)

Variables	1	2	3	4	5	6	7	8	9	10	Driving Power
1	1	0	0	1	0	0	0	1	0	0	3
2	1	1	1	0	1	0	1	0	0	0	5
3	0	0	1	0	0	0	0	1	0	0	2
4	0	0	0	1	0	0	0	0	0	0	1
5	0	0	0	1	1	0	0	1	1	0	4
6	0	0	0	1	0	1	0	0	1	0	3
7	0	0	0	0	1	0	1	1	0	0	3
8	0	0	0	1	0	0	0	1	1	0	3
9	0	0	0	1	0	0	0	0	1	0	2
10	0	0	0	1	0	0	0	0	1	1	3
Dependence Power	2	1	2	7	3	1	2	5	5	1	

Figure 3
Final reachability matrix (Source: SmartISM software)

Variables	1	2	3	4	5	6	7	8	9	10	Driving Power
1	1	0	0	1	0	0	0	1	1*	0	4
2	1	1	1	1*	1	0	1	1*	1*	0	8
3	0	0	1	1*	0	0	0	1	1*	0	4
4	0	0	0	1	0	0	0	0	0	0	1
5	0	0	0	1	1	0	0	1	1	0	4
6	0	0	0	1	0	1	0	0	1	0	3
7	0	0	0	1*	1	0	1	1	1*	0	5
8	0	0	0	1	0	0	0	1	1	0	3
9	0	0	0	1	0	0	0	0	1	0	2
10	0	0	0	1	0	0	0	0	1	1	3
Dependence Power	2	1	2	10	3	1	2	6	9	1	

Figure 4
MICMAC analysis (Source: SmartISM software)

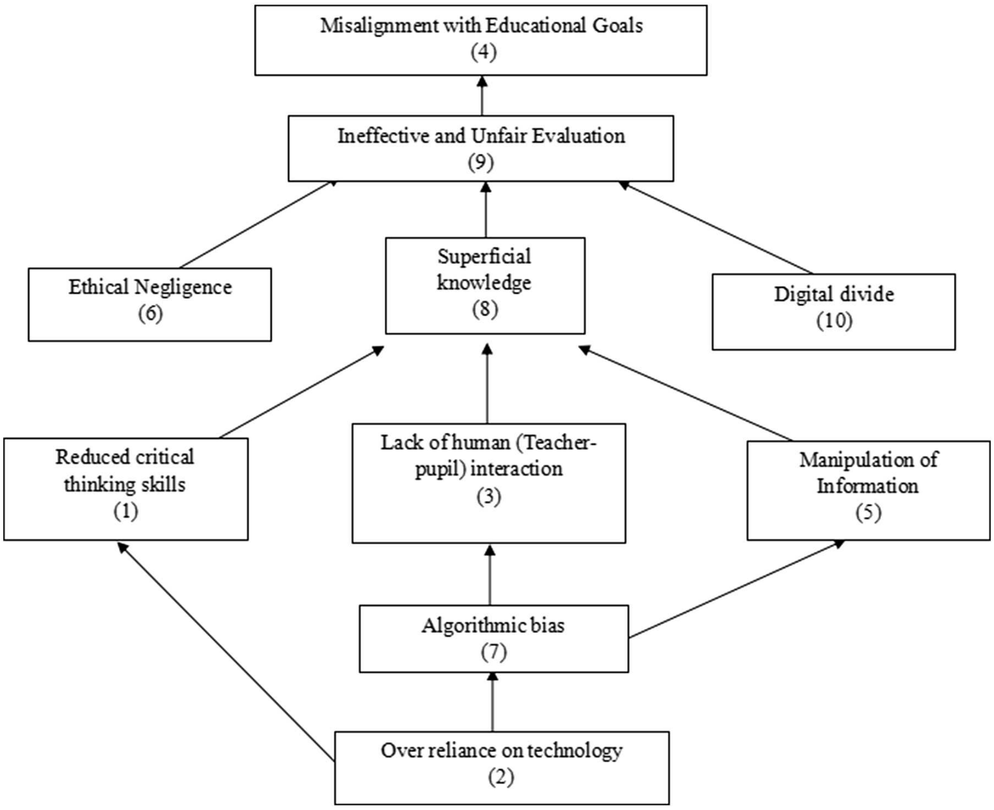


6. Discussion

6.1. Discussion of results

Overreliance on technology (2) at level VI has been found as the most crucial (driving) element in the hierarchy. It shows that the major challenge or concern is the uncontrolled dependence upon AI platforms for academic purposes by students. It further influences algorithmic bias (7) at level V, reduced critical thinking skills (1), and lack of human (teacher–pupil) interaction (3) at level IV. When reliance on AI or supportive technologies is used excessively in education to compute results, algorithmic bias may be introduced, which could affect how students are helped and answered. Algorithms have the potential to restrict students' exposure to a variety of viewpoints and methodologies by giving

Figure 5
ISM (Source: SmartISM Software)



preference to particular kinds of solutions or teaching strategies. This dependence may unintentionally perpetuate educational disparities by providing preference to particular learning styles or backgrounds. Dependence on AI to solve problems or retrieve information could stifle critical thinking and analysis. Instead of learning to think critically for themselves, students may rely too much on AI algorithms to provide them with fast solutions. This might impair their capacity for critical information evaluation, sophisticated problem-solving, or original thought. A greater reliance on AIEd could mean fewer possibilities for teachers to offer personalized learning, guidance, mentoring, and emotional support. The social-emotional and communication abilities of the students may suffer from this lack of human engagement. Learning requires direct interaction (emotional connection) carried out by the teacher and requires modeling or examples in the learning process to achieve academic success, while AI tools like ChatGPT cannot do this [22].

Algorithmic bias (7) at level V tends to influence the manipulation of information (5) at level IV. Students' perceptions and information can be distorted or constrained by algorithmic bias in AI-generated findings. A student's comprehension and learning outcomes may be impacted by biased algorithms that favor particular responses or interpretations. This kind of influence can stifle opposing ideas and support false or oversimplified information. One of the studies conducted previously has reviewed the evidence around algorithmic bias in education, beginning with the most heavily studied categories of race/ethnicity, gender, and nationality and moving to the available evidence of bias for less-studied categories, such as socioeconomic status, disability, and military-connected status [23].

The issue of superficial knowledge (8) at level III is dependent upon reduced critical thinking skills (1), lack of human (teacher–pupil) interaction (3), and manipulation of information (5) at level IV. Students' diminished capacity for critical thought as a result of their reliance on AI may encourage the acquisition of shallow knowledge. Learning requires creativity to create new ideas and innovations that are given to students to obtain feedback that can be developed by individuals, while AI tools do not have the creativity that humans have [22]. Deep engagement and analysis may be discouraged when information retrieval and problem-solving are primarily handled by AI. Quick answers may be more important to students than comprehending underlying ideas, which could lead to memorization and shallow knowledge rather than critical inquiry. Lack of human interaction between teachers and students as a result of AI dependency may lead to reduced personalized learning and mentoring that are essential for developing students' critical thinking abilities and deeper comprehension. If AI is used too much for feedback and instruction, students may not have as many opportunities to ask insightful questions, participate in thought-provoking debates, or receive individualized support. This may lead to a cursory understanding of ideas and impede the growth of critical thinking and social skills necessary for thorough learning. Limited exposure to multiple perspectives due to manipulated information can occur when students are exposed to selective information presentation that may distort facts or prioritize particular viewpoints. This may impede their capacity to acquire a sophisticated comprehension of intricate matters and encourage dependence on obfuscated or insufficient data.

The problem of ineffective and unfair evaluation (9) of students at level II is dependent upon ethical negligence (6), superficial knowledge (8), and digital divide (10) at level III. When students use AI for academic purposes, such as making assignments and referring the copied content, unethical behavior on their part might lead to unfair and inefficient evaluations among all students. Academic integrity is compromised by relying too much on AI to complete jobs like plagiarism and shortcutting, which could lead to unjustified grade inflation. Students who respect moral principles or do not have access to AI resources may be negatively impacted by this disparity. Test scores may be inaccurate in capturing students' genuine comprehension when they rely on AI to provide them with fast answers and superficial understanding. Superficial knowledge leads to erroneous assessments of students' desirable intellectual potential and development, missing important abilities and more profound understandings. Students' assessments are unfair and ineffective in part because of the digital divide. Lythreatis et al. [24] explain the factors affecting the digital divide can be classified into three different segments and nine main categories: sociodemographic, socioeconomic, personal elements, social support, type of technology, digital training, rights, infrastructure, and large-scale events. Out of all factors, education has been linked to the digital divide the most. Some students may find it difficult to fully engage in online learning or to use AI capabilities utilized in education due to unequal access to technology and internet resources. This discrepancy may result in divergent academic outcomes for the pupils involved, placing those without digital access at a disadvantage relative to their classmates. The second aspect is that the students relying on AI for assignment submissions must bind with ethical integrity defined in the educational context so that those students who don't have access to it can be evaluated on the same platform.

Misalignment with educational goals (4) has been found as the most dependent element at level I, which means that ultimately all problems and challenges are influencing this major problem. Misalignment with educational goals can result from the use of AI in student evaluations, which can be ineffective and unfair (9) overall. Education's main goal is to equip students with the values, knowledge, and abilities needed for lifelong learning, social contribution, and personal growth. It seeks to develop ethical consciousness, critical thinking, and creativity in order to overcome obstacles, make wise choices, and positively impact society. The beyond-required technology dependence somehow does not fulfill this purpose of education. The mismatch of actual performance and the evaluation has the potential to skew educational results by taking attention away from encouraging thorough learning and individual development. The integrity of education may be compromised if students choose to prioritize manipulating the system over actual academic participation.

6.2. Discussion of suggestive implications

In the realm of education, the integration of AI holds immense potential to revolutionize learning experiences and outcomes. AI can analyze vast amounts of data, personalize learning pathways, and provide real-time feedback, thereby catering to diverse student needs and enhancing educational efficiency. However, alongside these benefits, it is crucial to strike a delicate balance between the deployment of AI and the oversight of human educators. This balance is essential to mitigate inherent biases, ensure fair learning opportunities, and foster the development of comprehensive knowledge and critical thinking skills among students.

One of the primary concerns regarding AIEd is the potential for bias in algorithms. AI systems are designed to make decisions based on patterns and data inputs, which can inadvertently perpetuate biases present in the data. This is particularly problematic in educational settings, where unbiased assessment and equitable learning opportunities are paramount. An overdependence on AI for personalized instruction could discourage critical thinking if students simply expect algorithms to provide answers rather than engage in deeper active learning. To address this challenge, it is imperative that AI algorithms are continuously monitored, audited, and refined to minimize biases and ensure fair treatment for all students, regardless of their background or circumstances.

Furthermore, while AI can enhance learning through personalized recommendations and adaptive learning platforms, it must be complemented with opportunities for students to engage in autonomous research and critical thinking. Developing strong critical thinking skills requires students to explore diverse perspectives, question assumptions, and draw independent conclusions. Therefore, educators must strike a balance between AI-driven instructional methods and fostering environments that encourage curiosity, exploration, and deep learning.

Moreover, meaningful teacher–student interactions play a pivotal role in education. These interactions are not merely about delivering content but also about mentorship, guidance, and fostering socio-emotional development. AI can support teachers by automating routine tasks, providing data-driven insights into student progress, and facilitating personalized learning experiences. However, human educators bring empathy, creativity, and the ability to inspire and motivate students in ways that AI cannot replicate. Therefore, effective educational practices must integrate AI as a tool to augment rather than replace human teaching.

To provide students with a well-rounded education that prepares them for future challenges, educators must also consider the ethical implications of AI use. Ethical considerations include transparency in how AI systems operate, ensuring data privacy and security, and safeguarding against unintended consequences of AI-driven decisions. Upholding ethical standards in AI applications not only protects student rights but also fosters trust in educational institutions and technology providers.

The swift advancement of AI demands the creation of comprehensive teacher preparation programs that are adapted to the particular difficulties presented by integrating AI in the classroom. One major obstacle to successful deployment is educators' lack of expertise with AI tools, which frequently leads to less-than-ideal use of these tools. The establishment of organized training programs that emphasize improving educators' ability to use AI effectively and responsibly is necessary to address this. In order to ensure alignment with educational aims and prevent an excessive dependence on technology, such programs ought to enable educators to critically evaluate AI-driven systems. These programs will embrace the benefits of technological innovation while upholding the integrity of conventional educational ideals by giving educators the tools they need to successfully integrate AI into their teaching practices.

Moreover, closing the digital divide is essential to ensuring equitable access to AI-powered educational resources. Disparities in access to technology can exacerbate existing inequalities in education, limiting opportunities for students from underserved communities. Bridging this gap requires concerted efforts to provide equal access to devices, reliable internet connectivity, and training for both students and educators to effectively utilize AI tools.

Addressing this issue requires collaborative efforts between governments, technology companies, and educational institutions to ensure universal access to AI-powered resources. Fostering inclusion requires forming collaborations to subsidize or offer free access to these technologies for marginalized communities. These programs will make it possible for underserved children to take advantage of individualized learning experiences and problem-solving educational technologies by lowering obstacles to AI adoption. Thus, this strategy supports the overarching goal of guaranteeing that everyone receives an equal education, enabling each student to realize their full potential in a world that is becoming more and more AI-driven.

Additionally, privacy issues arise due to the monitoring capabilities inherent in many AI systems for education. These technologies often track student behavior, engagement, and performance data, leading to potential misuse or unauthorized access to sensitive information. Consequently, the ethical implications of such monitoring practices necessitate careful consideration to protect students' privacy rights and ensure the responsible use of AI in educational settings.

Ethical considerations are needed to identify and mitigate biases, ensure equitable access for all students, and preserve meaningful human interaction, both of which are vital to promoting real learning and personal growth. By proactively addressing such challenges, AI can enhance education when deployed responsibly and for the right reasons.

7. Conclusion

AI holds tremendous promise for transforming education; its integration must be approached with careful consideration of its implications. By striking a balance between AI integration and human supervision, educators can harness the benefits of AI while mitigating risks such as bias, ensuring equitable learning opportunities, and fostering the development of critical thinking skills. The study's focus on creating hierarchical models of these interactions provides policymakers with actionable insights on where to intervene, making the findings particularly useful for designing more balanced and equitable AI policies in education. This approach requires ongoing collaboration between educators, technologists, policymakers, and other stakeholders to navigate ethical dilemmas, address technological challenges, and maximize the positive impact of AI on education. The systems approach of problem-solving is a suitable tool to deal with such situations as cutting-edge complex challenges and realizing the interactions based on influence among these can help to draw certain clarity to facilitate decision-making and policy planning. The novel contributions of this research to advancing the field of AI in education are multifaceted and crucial to furthering current understanding. This study presents a unique approach by utilizing ISM to reveal the hierarchical relationships between various elements impacting the quality and value of education. ISM is one of the popular techniques under systems tools to reduce the complexity involved in decision-making. Hierarchical relationships among the elements clearly describe the influential/dependable role toward others. Students have developed a habit of surfing the browser for answers or assignments, getting several sources, and choosing anyone for reference. Now AI has taken this task to the next level, where, based on a selective algorithm, direct answers and clarity can be attained. This has further reduced the efforts students put into searching for knowledge and checking for the appropriateness of the answers provided. This cannot be denied that there are positive sides to such technologies. Anywhere, anyone can have access and extract information about any corner of the world. This is most popularly connected with the concept of informal learning. However, in light of education, the purpose of formal education cannot be neglected in which teacher–student interaction is not merely about gaining subject knowledge but also about addressing several other associated needs. In no sense, access to AI must be engaged in education, which can hamper the true essence and objectives of education. Ultimately, by adopting a thoughtful and balanced approach, we can create learning environments that empower students to thrive in a rapidly evolving world while upholding principles of equity, fairness, and ethical responsibility. There are some advanced ISM techniques known as fuzzy ISM and total ISM. The fuzzy ISM considers the dominance of influence among the pairwise elements rather than only considering the binary form of whether a relationship exists or not [25]. The total ISM considers some significant transitive links in the final model on the basis of experts' opinions, and the interpretations about the influence or association are also written in the links. The emphasis on both qualitative and quantitative analyses enhances the robustness of this study and offers future researchers new avenues for expanding the appropriate role of AI in creating more effective educational environments. Future researchers can take up these advanced techniques in their research work. Another limitation of this research work is that it fails to statistically validate the research results, which can be fulfilled by future researchers through the usage of structural equation modeling.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Sneha Seth: Conceptualization, Software, Formal analysis, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Hans Kaushik:** Methodology, Validation, Investigation, Writing – review & editing, Supervision, Project administration.

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